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Technology interdependency in the United Kingdom's low carbon energy transition

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ABSTRACT

The role of different technologies in a future low carbon energy system is determined by numerous factors, many of which are highly uncertain. Their deployment may be a function of dependency on other technologies, or competition, or wider system effects. In this paper, using a UK example, we explore patterns of interdependency between technologies using a hierarchical clustering approach across multiple scenarios. We find that technologies compete in some instances, often on costs, cluster because they co-depend on each other, or emerge under all conditions, as robust options. Crucially, the broader scenario framing around carbon capture and storage (CCS) availability and climate policy stringency strongly influences these interdependencies.

1. Introduction

1.1. *Contending with technology-related uncertainties in low carbon transitions*

The diffusion of new technologies to enable the transition to a low carbon energy system is subject to numerous uncertainties. Many countries are grappling with the options available to move energy supply to one that is zero emission [1], where different solutions emerge depending on factors relevant to national circumstances and assumptions about technology commercialisation. The timescales for this transition are also squeezed, with Paris Agreement targets suggesting net-zero emissions by, or soon after, 2050 [2]. Therefore, decision makers have to contend with both technological uncertainty and short timescales, not suited for long term system transition [3], whilst moving beyond incremental policies to real structural change within socio-political constraints [4].

Determining the future role of technologies used across the energy system is an important exercise for a number of reasons. Firstly, it can help demonstrate the plausibility of different technology pathways to decision makers. This is important in the context of deep decarbonisation by mid-century [1], a timeframe that many countries have yet to fully consider but will increasingly need to, as per Article 4.19 of the Paris Agreement [5]. Modelling analyses during the 2000s in the UK certainly helped determine multiple technology pathways that could deliver 60% [6] and then 80% [7] reductions in green house gas (GHG) emissions, relative to 1990 levels. This provided an important evidence base that provided confidence for, and underpinned, climate action legislation. Secondly, it can orientate the research and policymaking community in a certain direction, pointing to technology focus areas for R&D and demonstration budgets. A recent example has been the increase in research on greenhouse gas removal (GGR) technologies, with the UK research council, NERC, launching a large programme of work.[1] This research direction is very much in response to the ubiquitous deployment of such technologies in energy systems analysis, notably from Integrated Assessment Models (IAMs) [8,9].

However, many of the prospective technologies for the low carbon transition may be conceptual, partially demonstrated and at a very early stage of technology readiness, or only playing a niche role in the current system. This means large uncertainties exist concerning the role that technologies play, driven by many different factors. Take the example of solar; when Lewis [10] discussed its prospects, highlighting some of the key barriers for widespread use, including costs of \$0.25–0.30 per kilowatt-hour (kWh) compared to other generators at \$0.03-\$0.05, he, like key scenario providers such as the IEA, would have had difficulty envisaging this technology now competing with fossil generation 10 years later.

The question is how do the many technologies recognised as important for the low carbon transition play out together in the same system? The uncertainty around R&D, commercialisation, policy

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[1] NERC GGR Research programme, http://www.nerc.ac.uk/research/funded/programmes/ggr/.

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support, and social acceptability means that there are numerous eventualities in terms of system design and technology portfolios. Taking the prevalent example of carbon capture and storage (CCS) included in many climate mitigation scenarios [11], this is subject to all such uncertainties, including techno-economic factors [12]. Their impact on technology deployment will have different degrees of influence on the role of alternative competing technologies. This raises the question of how technologies or technology groupings interact, and whether they enable others, or compete. Possible examples are easy to identify (e.g. in a severely carbon constrained world and without CCS, would steam methane reforming be possible for hydrogen generation?), whilst others may be less obvious. Furthermore, inter-temporal dependencies may emerge, where specific technologies and their use in the system rely on earlier deployment of others.

1.2. Characterising technology uncertainties in energy modelling

Improved performance and cost reduction across technologies and their deployment in different societies is complex, and covered extensively in the fields of technology innovation and socio-technical transitions [3,13,14]. However, energy system models, such as that used in this study, typically make simplifying assumptions about the improvements in costs and performance based on exogenous single factor learning curves, and historical precedents in terms of deployment. In other words, there is limited attempt to model other factors, such as the innovation and learning process in national scale modelling, largely due the analysis scale and the complexity of process.

Without endogenising these effects, it is still possible to capture the uncertainty of the assumptions on technology learning and deployment in the energy system context, using different approaches. These approaches can provide a view of the many different system configurations, and help to understand the interdependency between technologies across the system. Most UK modelling analyses have focused on the development of traditional scenario analysis to explore distinctive low carbon transitions, either for the system as whole [15,16] or for specific sectors [17–19]. The use of uncertainty techniques have been less widely applied to scenario analysis [20], but are becoming increasingly recognised, both by researchers [21] and decision makers [22], as critical to facilitating more robust decision making. A recent review of the application of different uncertainty methods highlights some of the key modelling approaches deployed [23].

Global sensitivity analysis (GSA) is one such method, to assess and rank energy system uncertainties (see e.g. Marangoni et al. [24] for an integrated assessment modelling approach). In the UK context, Fais et al. [25] employed this approach across binary technology and resource dimensions, in order to explore which low-carbon technologies and resources had most influence on energy system development under emission reduction targets and the interaction effects between different low carbon options. The analysis highlighted complementarities and substitutability between technologies, critical options that are robust to uncertainty, wider system effects, and path dependencies.

Pye et al. [26] explored the potential for uncertainties across technologies and resources to undermine reduction targets, if policies were not robust to such uncertainties. The analysis also highlighted, via a GSA approach using multivariate regression analysis, which uncertainties had the largest influence on meeting decarbonisation goals. Usher [27] undertook a similar analysis, using a GSA known as the Morris Method, to explore which model uncertainties across a range of technology and resource groups influenced the model solution the most. Similar to Pye et al. [26], biomass resource availability and gas price proved to be highly influential, as did the CO_2 emission constraint.

While the above analyses focused on parametric uncertainty, other studies have been undertaken to explore uncertainty relating to model structure. The Modelling to Generate Alternatives (MGA) technique [28], with initial application in other fields, has been increasingly used for energy system analysis [29,30]. In the UK context, using a MGA technique, Li and Trutnevyte [31] identified many possible near-optimal pathways to decarbonising the power sector, highlighting how system choices are strongly influenced by the model structure and formulation of optimality.

Different approaches to uncertainty assessment provide useful information about the impact of uncertainties on model results, and particularly from the GSA analyses, the ranking of uncertain assumptions based on solution influence. However, these analyses typically provide fewer insights into the explicit enabling or competitive relationships between technologies or technology families in different systems, and the impacts of deployment of one type of technology on another. The focus of this paper is to explore the relationships between technology choices across different system pathways, to understand potential interdependencies.

1.3. Overview of the paper

In this study, using the Energy System Modelling Environment (ESME), we consider these issues for the energy system transition in the United Kingdom, framed to meet the current policy goal of at least an 80% reduction in GHGs in 2050 [32]. The research question tackled in this paper is 'Under a transition to a low carbon energy system, what technologies are typically deployed in combination or competition, and from these interdependencies, what are the insights for policy stakeholders?' We investigate the interplay and interdependencies between different technologies and technology families by simulating a large number of plausible pathways under uncertainty. For example, for the deployment of technology X, influencing deployment may be the characteristics of technology X, those of technologies Y and Z, and/or the broader system e.g. carbon price signal, resource availability etc. To determine the extent to which Y and Z influence the deployment of X, we use clustering analysis across the many simulations.

The paper is structured as follows; section 2 provides a description of our approach to modelling technology-focused scenarios and analysing interdependency between different groups. Results of the analysis are presented in section 3, followed by a discussion on the insights of the analysis for policy (section 4), and concluding comments (section 5).

2. Methodology

With our focus on technology interdependency in an energy system, we use the ESME model to run multiple scenarios based on a range of techno-economic uncertainties. These pathways are then analysed, using a hierarchical clustering approach, to analyse interdependency of technologies.

2.1. The ESME modelling framework

ESME [33], is used due to its whole system representation and integrated structure, both of which are necessary to reveal interdependency between sector action and technology deployment. The model is technology-explicit, thereby providing a sufficiently detailed representation of technology groups, to better understand the characteristics that enable deployment. ESME also features a module for simulating large numbers of runs to explore parametric uncertainty of model inputs, through Monte Carlo sampling [26,34]. In addition to research use, ESME analyses have also informed energy policy and strategy in the UK, both for the Department for Energy and Climate Change [35],[2] and the UK Committee on Climate Change (CCC) [36,37]. The ESME model was originally developed by the Energy

[2] The department now covering the DECC function is the Department for Business, Energy and Industrial Strategy (BEIS).

Technologies Institute (ETI), a public private partnership between Government and industry, and developed and used in conjunction with a range of research organisations.

Built in the Advanced Interactive Multidimensional Modelling System (AIMMS) environment, the model uses linear programming to assess cost-optimal technology portfolios. The exploration of uncertainty (capital expenditure levels, fuel costs and resource potential e.g. biomass imports) is focused across the technology groups. The number of technologies total around 150. Energy sector representation is typical of other similar models, and includes power generation, industry, buildings, transport and other conversion sectors e.g. biofuel production, hydrogen production. The model endogenously determines how to meet a set of exogenous energy service demands in a cost-optimal manner, through investment in end use technologies (including efficiency measures), and the production and supply of different energy forms. Central technology cost projections are exogenously defined, based on cost reductions envisaged from a move to a low carbon system, with characterisation of the uncertainty of such estimates (as discussed below). Further information on the sector structure and data sources used in the model can be found in the ESME documentation [38].[3]

2.2. Modelling uncertainty

Within the ESME model, we construct a number of scenarios using the inbuilt uncertainty characterisations across different techno-economic parameters, with a focus on costs, including capital expenditure (capex) and energy commodity costs. Other uncertainties applied here for the scenario generation include specific technology build rates and biomass resource availability. Build rate uncertainty for CCS and nuclear in particular reflects that many other factors determining deployment in addition to cost, with such technologies not market-driven in the same way as, for example, renewables. Resource limits on domestic and imported biomass are also included. These assumptions are set out in Table A1 in Appendix 1.

In the main, parameter ranges are established for mature (± 10%), new (± 30%), and novel/emerging (± 50% or more) technologies (see Appendix A1). For example, a combined cycle gas turbine (CCGT) plant has a relatively narrow cost range, as it is well understood given its maturity, compared to the same plant with CCS, which has a much wider range. The range distribution is sometimes asymetric, where for a technology it is unlikely that we would observe cost increases to the same extent as reductions. It is worth noting that in our analysis the range of the uncertainty considered is more important than other characteristics of the distribution – the aim is to generate many scenarios with different parameter values, but not draw any conclusions about how likely specific combinations might be.

The uncertainty distributions in 2050 are sampled using the Monte Carlo technique. For each simulation, values for intermediate years (prior to 2050) are determined based on interpolation back to the base year (2010) value based on an index using the shape of the original 2010 to 2050 trajectory. The interpolation of an uncertain value in 2050 back to 2010 is a simplification for reasons of model tractability. The increase or decrease in costs and build rates between now and 2050 will of course not follow a linear trajectory but may be subject to volatility over this time horizon, with sudden cost breakthroughs, or rapid increases or declines in deployment, often due to political driven policy change.

600 simulations are run, the number based on earlier analyses to determine coverage of the uncertainty space [39]. While most of the distributions are independent, some are correlated during the sampling procedure. This is to ensure that technologies that are similar in nature (for example, a light duty electric vehicle and an electric car) move in the same direction.

2.3. Scenario definition

The 600 Monte Carlo simulations are then modelled for a set of three scenarios (Table 1), resulting in 1800 model runs in total. Scenarios reflect major areas of uncertainty that we want to hold constant due to their large impact on the system, in order to explore whether technology interdependencies change when a step change in the parameter values is introduced. Two scenario dimensions are represented – i) climate ambition, and ii) the availability of CCS.

Both CP and NCCS meet the UK's legislated climate ambition of at least an 80% reduction in GHGs in 2050, and the interim carbon budgets needed to deliver the long term target [40]. The difference is that CP allows for large-scale CCS deployment, while NCCS does not. The testing of this assumption is important in the UK context, where CCS is often chosen because it offers a highly cost-effective pathway [15] and because the credibility of CCS and BECCS (bioenergy with CCS) deployment at scale is coming under increasing scrutiny [41,42]. F2R provides a lower climate ambition case, due to a ‘failure to ratchet’ ambition, to explore prospects for deployment under weakened ambition and therefore lower incentives for mitigation. The resulting level of ambition in 2050 is only marginally higher to that which is required in 2030, under the UK's 5th Carbon Budget. Both CCS availability and climate ambition are likely to lead to very differently configured systems, allowing us to observe whether different technology interdependencies emerge.

2.4. Clustering analysis

Clustering algorithms can be used to group scenario metrics based on information in the dataset about those metrics and their relationships [43]. The objective is that cluster groups will have metric included that are similar to each other, and different enough to metrics in other groups. Given the research objective on technology interdependency, clustering is used to group metrics based on the strength of their correlation with each other. These are metrics that characterise the different pathways, for example the level of deployment of different technologies or level of use across energy resources. The correlation between such metrics allows us to observe, for example, whether certain technologies increase or decrease deployment simultaneously, whether their deployment moves in opposite directions or whether their deployment appears to be independent from each other.

Specifically, we use agglomerative hierarchical clustering, which is a common clustering algorithm and has been applied, for example, in the energy and buildings field [44,45]. In this approach, clusters are nested meaning that they are merged successively. Each model metric is clustered with its closest neighbour, meaning where the strongest correlation is found. This cluster pair is then grouped with another, and so on, until a single cluster is reached that includes all metrics. This tree-like construction of nested sub-clusters can be visualised as a dendrogram, as shown in Appendix A3, representing the structure of the relationship between data metrics. The dendrograms use a dissimilarity metric to show strength of correlation, with a low value highlighting a higher positive correlation.

While clusters indicate where the deployment of technologies increase or decrease simultaneously, the algorithm used does not provide insight as to whether the deployment of individual technologies contributes to the energy system in a meaningful way. In other words, a

[3] The data input parameters are available at http://www.eti.co.uk/programmes/strategy/esme. Note that these data assumptions are for v4.3, and in the main, are consistent with the input assumptions for v4.2, which is the version used in this analysis. The key updates in v4.3 are shown in the ‘change log’ at the end of the document; all have been integrated into the version we are using (v4.2). Nuclear costs, and uncertainty distributions are based on our own work (see Appendix A1), and therefore will differ from those published under the released v4.2.

Table 1
Scenarios for modelling.

Scenario Name	Climate ambition*	Technology availability
NCCS (No CCS)	−80% GHG reduction in 2050 (rel. to 1990), −53% in 2030	All low carbon options except CCS
CP (Climate Policy)	−80% GHG reduction in 2050 (rel. to 1990), −53% in 2030	All low carbon options
F2R (Failure to ratchet)	−64% GHG reduction in 2050 (rel. to 1990), −48% in 2030	All low carbon options

* The 2030 value includes international shipping and aviation emissions, sectors which are not included in the UK carbon budgets but which are included in the 2050 target. To ensure consistency, the 2030 reduction above is on the same basis as the 80% target, and include international transport emissions. This means that the reduction level is lower than the UK 5th Carbon Budget target of around 57% in 2030.

cluster could include a power generation technology that barely contributes to overall electricity supply, together with a transport technology that is key for the transport sector. Therefore, further analysis of the results is required to complement the cluster analysis. It is also informative to determine negatively correlated metrics, to identify deployment of groups of technologies moving in opposite directions. To do this, we constructed a proximity matrix based on the correlations between any two clusters, represented by the mean of the metrics included.

In this paper, the clustering approach is applied to two datasets. The first uses a range of metrics directly from the model, chosen for their representation of the main technologies and fuels deployed in pathway simulations. A second set of metrics is derived from the model outputs using a decomposition approach called logarithmic mean Divisa index (LMDI) [46]. This method allows for an understanding of which drivers are responsible for the change in emission levels of different subsectors over time, including energy efficiency, conversion efficiency or decarbonisation of the energy supply. Decomposition approaches, such as LMDI, have been used for decades to study how changes in the level of a variable (e.g. emissions, energy use) can be attributed to the changes in its drivers [47], including in energy systems analysis [48–50]. Both sets of metrics are listed and further described in Appendix A2.

3. Results

Here we first present the results of the clustering analysis. We first discuss the LMDI clustering analysis, followed by the clustering of the direct model metrics.

3.1. Clustering of LMDI wedges

LMDI analysis provides an indicator of the contribution of different types of mitigation "wedges" [51] across sectors in any given simulation. These wedges allocate emission reductions across different sectors to three different types of measures *m*: (1) Reduction of energy demands (D_s) (2) improvements in efficiency (F_s/D_s, includes electrification effects) and (3) decarbonisation (carbon intensity of final energy), $CO_{2,s}/F_s$). The emissions for end use[4] sectors are thus expressed:

$$CO_{2,s} = D_s \cdot \frac{F_s}{D_s} \cdot \frac{CO_{2,s}}{F_s}$$

The LMDI formulation allows the allocation of mitigation efforts to individual "wedges", without leaving a residual. Mitigation between time t_1 and t_0, for a specific sector s and measure m can be calculated from:

$$\Delta CO_{2,s,m} = \frac{CO_{2,s,t_1} - CO_{2,s,t_0}}{\ln(CO_{2,s,t_1}) - \ln(CO_{2,s,t_0})} \cdot \ln\left(\frac{m_1}{m_0}\right)$$

The distribution of relative contributions of measures (that contribute at least 10% of mitigation in at least one model run) in 2030 and 2050 are shown in Fig. 1 for each scenario. Negative contributions suggest an increase in emissions, typically for energy service demands which rise over time and which the model cannot reduce.

Across the scenarios, the importance of electricity decarbonisation in both 2030 and 2050 (driving higher levels of electrification[5]) is evident. There are, however, also clear differences across the scenarios and the milestone years. Lack of any CCS applications and a stringent emissions target, for example, forces earlier power decarbonisation in all NCCS runs, whereas F2R, having the most flexibility of the three scenarios due to its lower target and full technology portfolio, can in some runs reduce the contribution from power sector decarbonisation down to 25% of the full mitigation effort. By 2050, much of this flexibility is gone and F2R relies even more on power sector decarbonisation than the other scenarios. Decarbonisation of the energy carriers used in the industry is another key mitigation measures with a wide range of contributions across the scenarios and runs, contributing on average 20–30% by 2030 in the scenarios that allow CCS technologies. Without CCS, however, the carbon intensity generally increases, turning this mitigation wedge into a source of emissions in most NCCS runs. For F2R, this mitigation measure has a very wide range, contributing from −30% (i.e. being an emission source) to 65% of all mitigation by 2030.

Other mitigation measures generally contribute less and vary more across scenarios and milestone years than between simulation runs. The differences produced by scenario assumptions are greater than those based on the parametric uncertainty distributions. For example, in 2050, decarbonisation of passenger car fuels contributes 12–21% of mitigation in NCCS runs, but no more than 9% in all the simulation runs in the two other scenarios. In other words, all the uncertainties captured in the hundreds of CP and F2R runs did not lead to a run that would have as much passenger car decarbonisation as all of the NCCS runs did, highlighting how strongly discrete, key assumptions can change the model results. The small range of contributing mitigation wedges in 2050 and the limited variation in contribution across the scenario simulation sets, few meaningful results are observed from the cluster analysis. Most of the calculated wedges play an insignificant role by 2050 and thus can contribute little to the cluster analysis. Conversely, assessing the relationships between the key wedges becomes easier to do manually (see below). This highlights that the mitigation effort, at the sector level, is not that responsive to uncertainty, either as imposed via the scenarios or parameters, although the flexibility from less stringent targets does see more wedges under F2R.

However, the correlations between individual wedges (see Appendix 4), on which the clustering is based, reveal some useful insights. Focusing on wedges that contribute most, in both RM and NCCS, early power sector decarbonisation is strongly correlated with continued power sector contribution and heat decarbonisation in 2050, suggesting a path dependency for the power sector contribution. Interestingly, there is no link to early heat decarbonisation, suggesting

[4] The equation remains the same for the conversion sector, but *Ds* in the above equation is replaced by the final energy output of the sector and F_s by the primary energy use of the sector.

[5] For example, in NCCS system wide electricity use accounts for 14% of the total energy use in 2020, and between 52 and 62% in 2050.

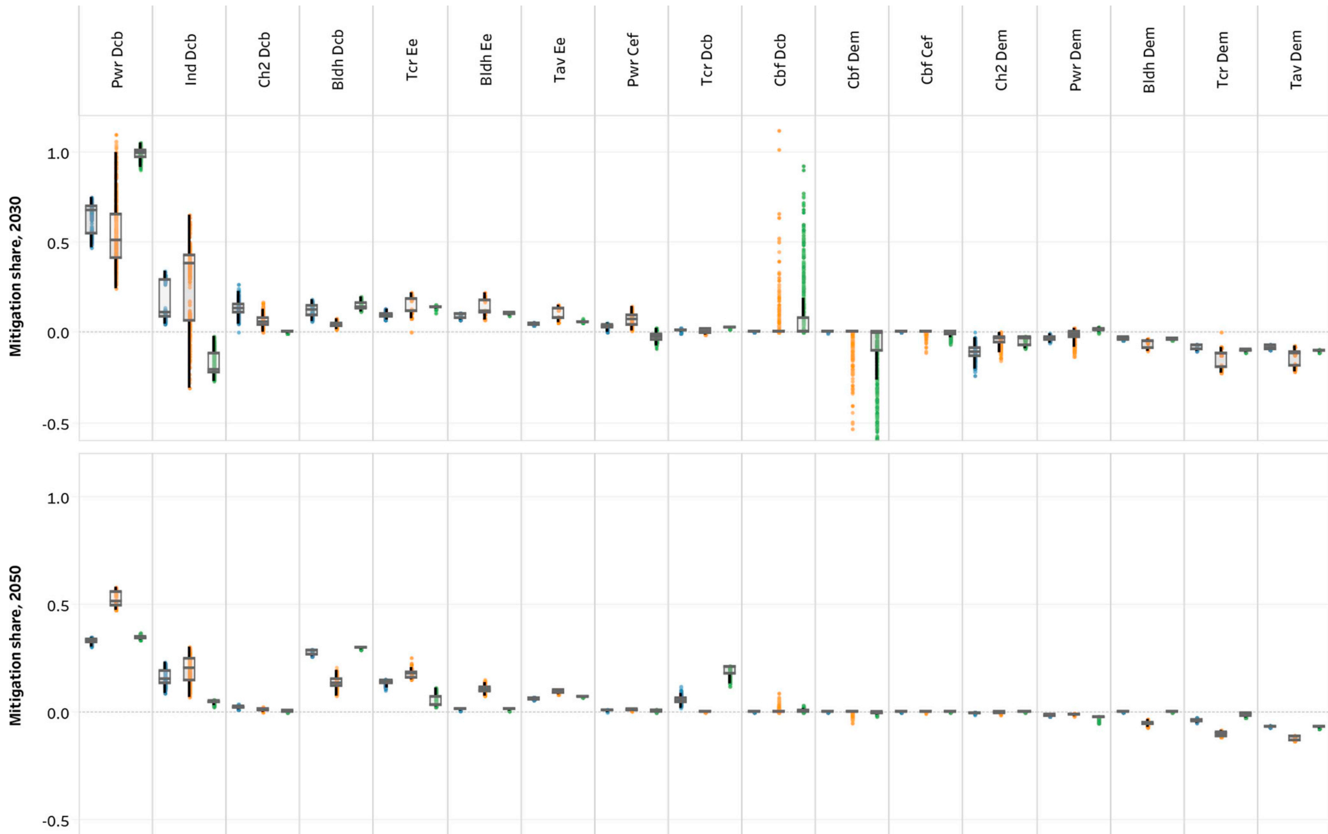

Fig. 1. Contribution of different mitigation wedges to emission reduction in 2030 (upper panel) and 2050 (lower panel, NCCS = green, CP = Blue, F2R = orange). Positive values represent a mitigation driver reducing emissions, and vice versa for negative value. The box corresponds to the inter-quartile range (IQR) and the whiskers represent the extent of values 1.5 times the IQR. Letters in the first part of the label denote sector [PWR = power; IND = industry; TCR = passenger cars; TAV = aviation; BLDH = building heat; CBF = biofuels production; CH2 = hydrogen production], while second part denotes type of driver [EE = efficiency improvement; DEM = demand reduction; DCB = decarbonisation] [6].

that the transformation of the heating sector requires a longer timeframe than power sector decarbonisation due to slower deployment rates of low carbon options, and higher costs. Decarbonisation of fuels in the industrial sector by 2050, in turn, is negatively correlated with decarbonisation of heat in the residential sector and power sector decarbonisation in the scenarios in which CCS is available. This suggests that CCS brings with it some flexibility to target mitigation at different part of the system, but the wedge analysis alone does not reveal what specific technologies contribute to this dynamic, which we investigate in the following section.

3.2. Clustering of model metrics

We move from the more aggregated mitigation wedges to clustering of metrics taken directly from the modelling. These are listed in Appendix A2, and primarily consist of different energy technologies and resources, based on their use in the system (in generation or consumption terms). Based on the hierarchical approach, the resulting set of clusters in 2050 are shown for each scenario-based dendrogram in Appendix A3, with results presented in Figs. 2 and 3.[7]

Fig. 2a shows six distinctive clusters under the No CCS (NCCS) scenario set of simulations. Where a cluster is negatively correlated to another cluster (based on a coefficient of less than −0.5), this is also indicated by a red arrow. The two largest clusters in terms of number of metrics, purple and orange, are negatively correlated. The purple cluster groups biomass resource levels with biofuel production for use in transport, including aviation, suggesting higher levels of biofuel production where biomass resource levels are higher. The orange cluster includes hydrogen use in the road transport sector and oil in aviation. The additional inclusion of cost metrics also suggests this is a higher cost cluster, due to use of electrolysis for hydrogen production, which is deployed when biofuel production is lower.

Building sector clusters include district heating (blue) and building electrification (yellow), which are negatively correlated, suggesting competition between technologies. However, the level of electricity use is quite stable across simulations, with a low distribution so competition is based on marginal changes. The building electrification cluster includes heat storage in buildings, and building retrofits, both important to reduce demand and manage electricity loads, and improve building performance for heat pump uptake. The other two clusters include transport sector electrification (sky blue), and renewable generation (green). The absence of negative correlations for these clusters highlights that they are not 'crowded out' and are typically prevalent in most simulations, due to the increasing importance of electrification, particularly in the absence of CCS. This is particularly true of transport sector electrification, with limited results spread (as shown in Fig. 2a box plot).

For the climate policy case with CCS availability (CP), the main difference in clusters, compared to NCCS, relates to hydrogen (H_2) production, now produced using CCS (Fig. 2b). A purple cluster reveals

[6] Excluding outliers, i.e. data points that are at least 1.5 times the interquartile range above/below 3rd/2nd quartile. There are a handful of runs like this, but not many.

[7] While we pre-defined the algorithm to search for 10 clusters, the number is not crucial because the dendrogram (built based on the correlation coefficients) retains the same structure irrespective of the cluster number. Only clusters.

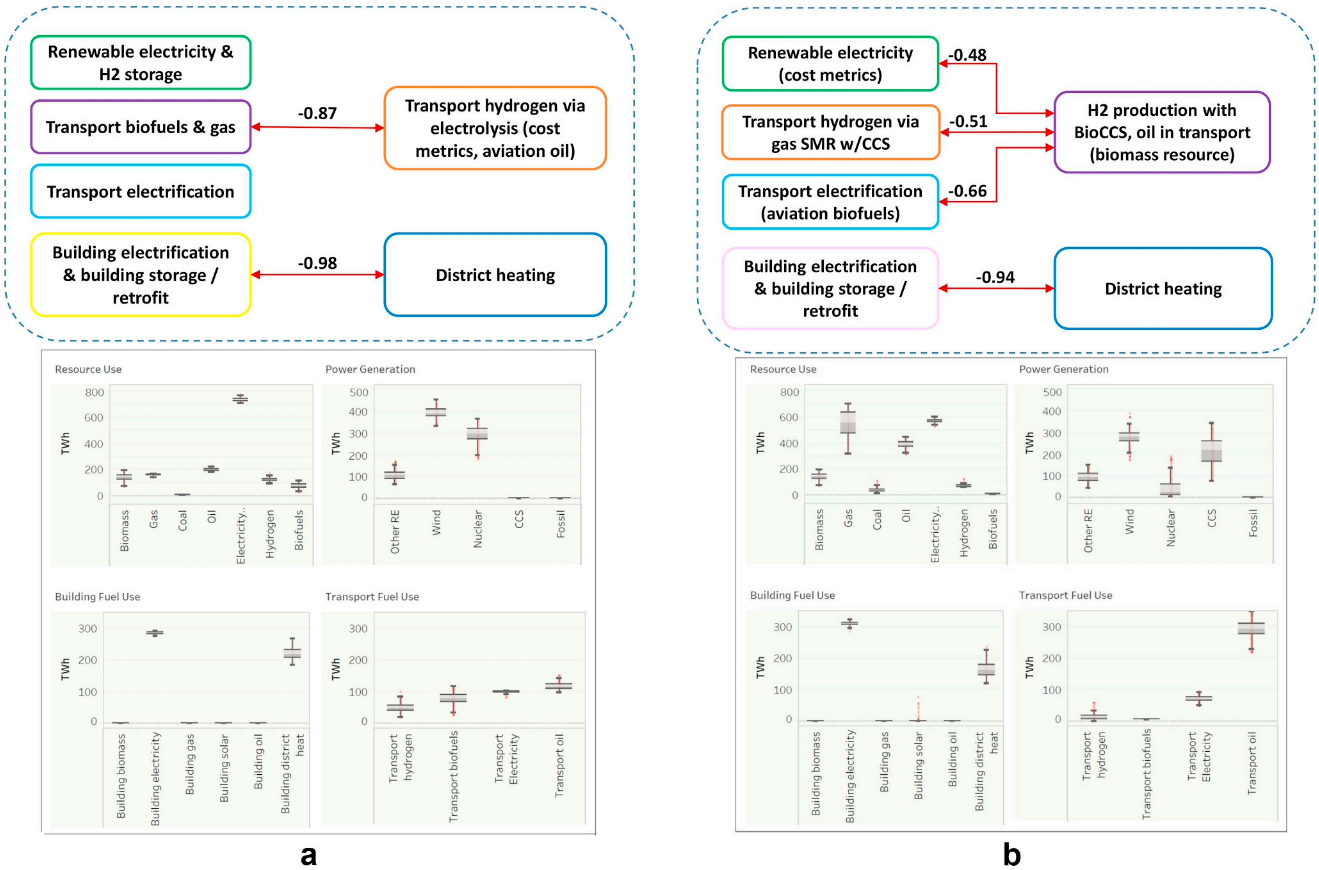

Fig. 2. NCCS and CP scenario clusters (top) and results distribution (bottom) in 2050. Clusters are identified in the top of the figure, with negative correlations shown by red connectors, the value indicating the correlation coefficient. More information on the technologies included in each cluster can be found in Appendix A3. The distribution of results underpinning the clusters are shown in the bottom part of the figures, with metrics (top left, going clockwise) on total energy use, power generation, building fuel use and transport fuel use.

biomass availability associated with bioenergy-based H_2 production with CCS, and transport oil use, indicating that more bioenergy resource increases it use for H_2 production with CCS, in turn allowing headroom for transport emissions and more oil use. This cluster is negatively correlated with three other clusters including H_2 production and use in transport (orange), renewable generation (green), and passenger car electrification (sky blue). These include clusters with a stronger focus on end use sector mitigation in the transport sector (orange, sky blue), including biofuels in aviation, partly required when offsetting from BECCS is lower. The renewables cluster (green) is associated with costs metrics implying higher cost in higher renewable deployment cases. This is not because the unit generation cost of renewables is higher than alternatives but due to the more cost-effective system wide mitigation (offsetting) that CCS with bioenergy is able to provide. Similar to NCCS, the building electrification cluster (pink) is one that also sees heat storage in buildings and retrofitting to reduce energy requirements, and is again negatively correlated with the district heating cluster.

Finally, we consider the F2R, which assumes a weaker climate policy, based on ‘failure to ratchet’ ambition. As with the CP case, a cluster (brown) emerges to include H_2 production with CCS for use in industry, and transport oil use, enabled due to emissions headroom. This cluster is negatively correlated with the pink cluster, which includes transport biofuel use. However, the use of these fuels in this scenario are relatively low, so do not have a huge impact on the results.

Biomass availability and its use by industry are clustered (olive green) with gas use in buildings, indicating that higher mitigation efforts in industry see a reduction in the need for action in the building sector. This allocation of bioenergy, which differs from the higher allocation for use with CCS under the CP case, suggests stringency has an important impact on resource allocation across sectors (as reflected in the discussion on flexibility across mitigation wedges). This cluster negatively correlates with the yellow cluster, which includes H_2 in industry, the electrification of buildings, and cost metrics. On the cost metrics this is not surprising given how influential biomass resource availability is on system costs. Finally, the pale pink cluster includes gas CCS, and is negatively correlated with a non-CCS generation cluster (green), highlighting competition between generation types.

4. Discussion

There are a number of insights that emerge from the clustering analyses. First, the approach provides a useful basis for understanding key interdependencies between different technologies and where these do not exist. Second, it highlights how the overarching scenario drivers appear to have a strong impact on patterns of technology interdependency. Third, the LMDI analysis highlights limited change in the pattern of sectoral contribution, and points to observed changes driven by scenarios rather than the uncertainty ranges across input parameters.

4.1. Technology interdependency revealed

Whilst all technology options can be deployed in a given pathway, the clusters indicate what technologies move together and so are interdependent, and therefore would have a tendency to deploy at relatively higher levels together, and in such instances of high deployment, identify other technology groups that deploy at lower levels (where

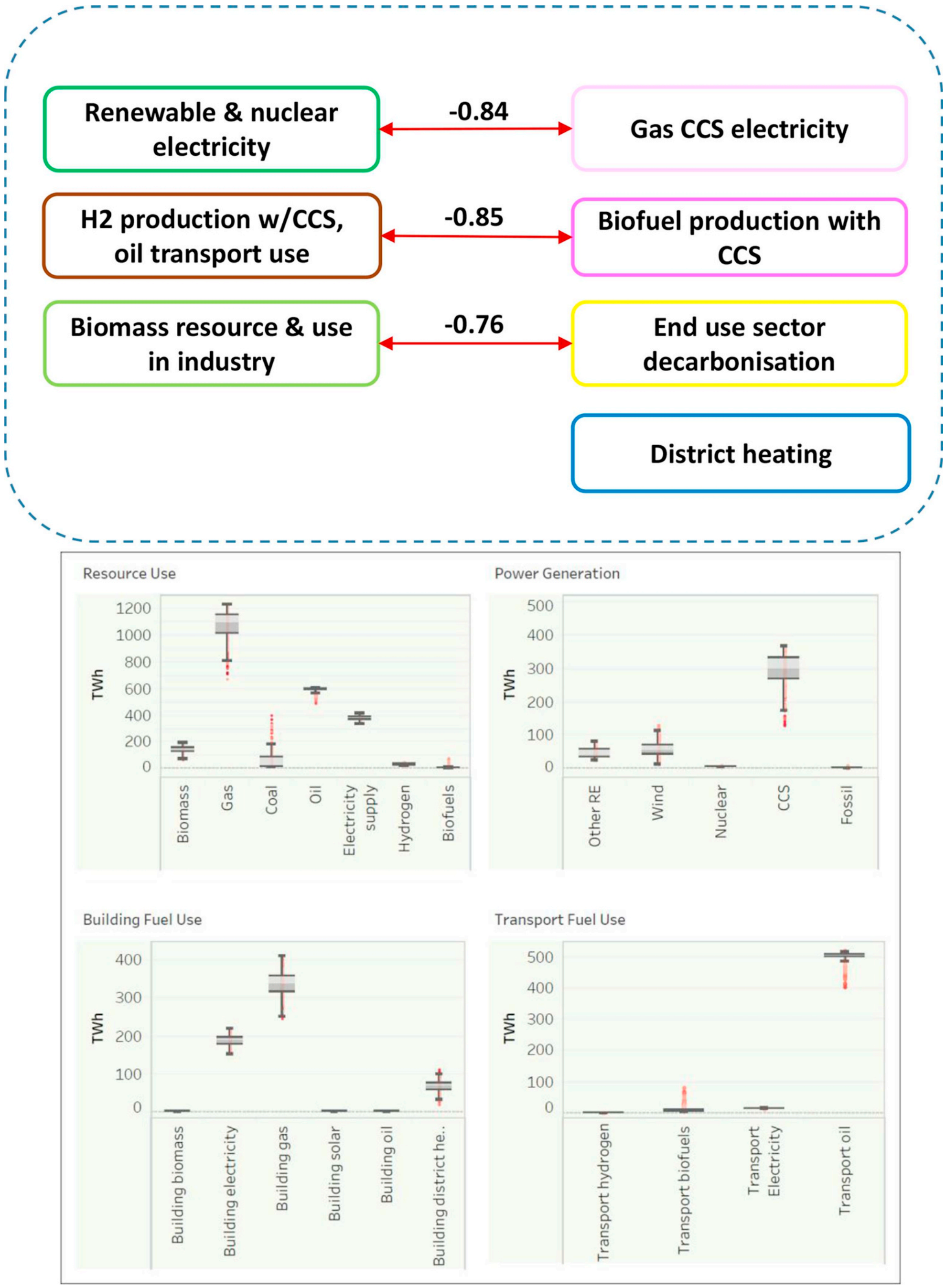

Fig. 3. F2R scenario clusters (top) and results distribution (bottom) in 2050. Clusters are identified in the left hand side of the figure, with negative correlations shown by red connectors, the value indicating the correlation coefficient. More information on the technologies included in each cluster can be found in Appendix A3. The distribution of results underpinning the clusters are shown on the right hand side, with metrics (top left, going clockwise) on total energy use, power generation, building fuel use and transport fuel use.

negative correlations are revealed). A clear example is for the buildings sector, where electrification is tied to building storage and retrofit, highlighting the requirement for the system to manage increasing intermittent supply and peak demand. The negative correlation with district heating suggests some competition between these systems depending on cost uncertainties. For both high ambition scenarios (NCCS, CP), these relationships hold.

Where CCS is not available (NCCS), three transport sector clusters emerge - biofuels, H_2 and electrification. The negative correlation between biofuels and H_2 clusters is driven by biomass availability, whereby higher availability leads to more biofuel production and use, and less H_2, which can only be produced via higher cost electrolysis. Where CCS is available, hydrogen from biomass gasification with CCS clusters with system oil use, and is negatively correlated with biofuel and electrification clusters. Dissimilar to NCCS, the H_2 production cluster here is most cost-effective, due to the biomass availability and system wide role of CCS in offsetting mitigation effort required in other sectors; hence the higher oil use in transport as CCS use increases.

For the power sector, analysis shows that wind generation always deploys at scale (between 40 and 50% of total generation in NCCS and CP), as the largest generation source in the absence of CCS, or in the top two generators where CCS is available, showing it to be fairly robust under all cases. In the NCCS case, renewable generation is clustered with H_2 storage, due to its role in production via electrolysis. Where

CCS is available, renewable generation is negatively correlated with CCS-based clusters; in F2R and CP, CCS directly competes with renewable generation, and indirectly in CP by providing more emissions headroom due to offsets, meaning less renewable generation for low carbon electrification in end use sectors.

4.2. Scenario drivers influence on interdependency

The above insights on technology interdependency are clearly impacted by overarching scenario assumptions for CCS availability and climate ambition. This is evident in some quite distinctive cluster patterns; for example, bioenergy availability is clustered with H_2 production using CCS under CP, but with biofuels production in NCCS, while in F2R, biomass availability is associated with its use in industry. This is because such assumptions have strong system wide effects. CCS combined with bioenergy provides negative emissions, which can offset hard-to-treat sectors that would require higher cost mitigation options.[8] In addition, important low carbon energy production is also provided, such as hydrogen or electricity production. Even high CCS cost-low bioenergy simulations in CP are lower cost than any simulation in NCCS. CCS for example is valued by the system to the extent that it brings the marginal abatement costs of mitigation in 2050 down to an average £450 per tCO_2 (range £320–595) in CP, from £1500 (£885–2115) in NCCS. The value of CCS, particularly with bioenergy, is reflected in a range of other analyses, both at a national [25,52] and global levels [8].

Similarly, the lower ambition in F2R see costs of £38 per tCO_2 (range £34–42), meaning lower incentives for a range of technologies, although CCS still plays a role. The absence of CCS (in NCCS) means cost uncertainty matters less, as the system has reduced flexibility and has to take specific options with limited prospects for fossil fuels.

In addition to highlighting the difference, the robustness of some insights are evident by the fact that they do not change across the scenarios. For example, the higher cost clusters are in each case negatively correlated with the clusters with more biomass availability. This is due to the high value of biomass in the system and its influence on energy system costs [53]. The building electrification clusters always see a similar composition, and are negatively correlated with district heating in the CP and NCCS cases. The absolute changes across simulations are indeed limited by the building sector being the end use sector with near total decarbonisation by 2050. Another similarity across scenarios is that a renewable generation cluster is identified for each scenario, although its composition typically differs, as do the clusters to which it is negatively correlated. In the 'with CCS' scenarios, it is negatively correlated with CCS dominated clusters, while in NCCS, it is not negatively correlated with any clusters but with a single technology i.e. nuclear generation.

The strength of scenario drivers also highlights that technology interdependency is more sensitive to broader analysis framing than the technology uncertainty ranges. This raises questions as to whether uncertainty ranges sufficiently cover a wide enough range or indeed the necessary types of system uncertainty.

4.3. Aggregation impacts on clustering results

While technology clustering (3.2) highlights how parametric uncertainty and scenario framing can reveal interdependency, the LMDI metrics suggest that these same uncertainties do not radically change the share of sector mitigation (i.e. technologies within the sector may change, but the total sector contribution does not). This either tells us something about the robustness of the results as to the level and timing of sector contribution, or suggests that the model is structurally predisposed to determining such patterns, despite the uncertainties introduced into the modelling. This lack of variation across wedges results in clustering being ineffective. As most simulations rely on a handful of key mitigation wedges, most wedges become meaningless for the clustering and the dimensions of the analysis are reduced to a level at which clustering does not provide much benefit. Conversely, focusing on the key wedges, it is possible to identify very strong correlation between specific wedges, which reinforce the relationships observed in the technology clustering. Additional observations are that scenario drivers have a stronger effect on the distributions than the technology level uncertainties, reinforcing the idea that the uncertainty distributions may be limited in range, and to the assumptions to which they apply.

5. Conclusions

This type of analysis provides decision makers with insights on the interdependencies of technologies, arising from competition on cost (electrification versus district heating), co-dependence (electrification plus storage), or system wide effects (absence or inclusion of key technologies e.g. CCS, policy ambition). Understanding interdependency in a system is important; it helps identify what technologies work together and which tend to compete, under different system level conditions. It also provides insights into why technology deployment may be low, if negatively correlated to a competing technology deployed at scale.

The negative correlations between biomass availability and higher cost clusters highlight the strong influence of this commodity on costs. Similarly, the negative correlation between CCS with bioenergy clusters and other end use options (in the CP case), for example for transport sector decarbonisation, highlight how such options might be significantly reduced by the inclusion of another (such as CCS). This type of approach therefore provides enhanced understanding of multiple pathways under uncertainty, through clustering options and revealing negative correlations.

There are a number of specific insights for UK policy. First, the prevalence of CCS, due its cost-effectiveness, suggests it is a critical technology to develop and scale. This is an important message – it is a clear opportunity. However, the inclusion of CCS also hides other solutions, reducing the diversity of option type, and delaying their deployment. There is a danger that the pervasive effect of this technology on the wider system as shown by this analysis is not fully recognised, which is problematic given the real risks of it not scaling in a timely fashion. It is not simply an alternative electricity generation option but one that can offset action in end use sectors (via BECCS), allow for a slower transition away from fossil fuels, and delays direct mitigation in end use sectors like transport. Arguably this analysis shows the need for robust action, given CCS' influence and risks of non-delivery, to ensure options that allow for dynamic policy making as the situation evolves [54]. Notably, recent Government projections perhaps underlie fading optimism as to the role CCS can play in the next 20 years, with almost no deployment envisaged prior to 2035 [55].

Second, interdependencies are strongly influenced by biomass resource assumptions. It is important to observe that this commodity has huge value in the analysis, and that its allocation varies markedly for given climate ambition and CCS deployment. Third, renewable electricity deployment levels appear less impacted by system level or technology uncertainty, highlighting the robustness of this technology as a major player for electricity generation in the long term. This is not the case for nuclear, which is much more dependent on the scaling or not of CCS. Given that wind generation is proven with rapidly falling costs, it appears an extremely robust option, which makes lack of UK government support for onshore wind all the more questionable.

Finally, the interdependency shown by clusters highlights some important insights on planning policy actions in parallel. High building

[8] Imported bioenergy is not fully carbon neutral, with 30% of total emissions from its use counted due to consideration of life cycle emissions. For domestic bioenergy, the accounted level is 10%.

electrification requires thinking about building efficiency and storage to allow for strong deployment of heat pumps. Hydrogen production is only cost-effective alongside CCS, allowing for gas steam methane reforming (SMR) technology or the opportunity to generate negative emissions via BECCS. Importantly, negative correlations between clusters do not indicate that policy makers need to take an either-or decision, but rather what technology groups may compete under different system configurations.

Whilst useful insights for policy, it is also worth highlighting the limitations of this type of techno-economic modelling. System choices are driven by rational economic choices and perfect information, with limited consideration of other barriers. In reality, there are a range of other factors that will influential deployment of different technologies, particularly in the socio-political domain. For example, many technologies are subject to political influence, such as onshore wind planning barriers in the UK and support for nuclear, or the lack of support for nuclear and push for renewables in Germany [56]. Community acceptance is an oft cited additional factor, linked to influencing the political agenda [57]. Other technologies have received very little support in the past due to range of governance and social factors e.g. district heating [58]. Therefore, the implementation of different strategies for decarbonisation will need policies designed that further consider some of the key issues around barriers, including convenience, choice and acceptance.

Reflecting on the analysis, future efforts could focus on widening both the existing uncertainty ranges and the type of uncertainties included in the simulations e.g. climate policy incentives, energy demands. It is interesting how narrow some of the results ranges were – and the comparative strength of the scenario drivers. Reflecting on the above point around socio-political uncertainty, further research on the interface between modelled and non-modelled uncertainties would appear to be a worthwhile avenue for research [59,60]. It would also be informative to consider scenario exploration techniques that gave stronger insights into the determinants of different clusters [61]. In summary, the use of clustering for enhanced understanding of how technologies interplay or not in a system context adds to the toolbox of modelling approaches that can assist decision makers.

Author contributions

S.P and I.K. developed the research idea and S.P. designed the research, with input from P.L and I.K. S.P set up and ran the ESME model. P.L developed the clustering analysis routines, with input on its application from S.P and I.K. S.P led the analysis of the results, with input from P.L and I.K. All authors were involved in the writing of the paper.

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Appendices

A1. Uncertainty parameterisation

The table below lists the input parameters subject to uncertainty distributions, with the distribution range in the right hand columns. Further information on the data input parameters can be found at http://www.eti.co.uk/programmes/strategy/esme. Note that these data assumptions are for v4.3, and in the main, are consistent with the input assumptions for v4.2, which is the version used in this analysis. The key updates in v4.3 are shown in the 'change log' at the end of the document; all have been integrated into the version we are using (v4.2). Nuclear costs, and uncertainty distributions are based on our own work, and therefore will differ from those published under the released v4.2.

The focus of the uncertainty assessment is on costs of technologies and energy commodities. Annual maximum build rate uncertainties are also applied to nuclear and CCS technologies whose deployment are subject to many additional factors e.g. planning, social acceptability, political support. The uncertainty distributions in 2050 are sampled using the Monte Carlo technique. For each simulation, values for intermediate years (prior to 2050) are determined based on interpolation back to the base year (2010) value based on an index using the shape of the original 2010 to 2050 trajectory.

Table A1
Model input parameter assumptions, and uncertainty ranges

Technology type	Technology	Parameter type	Values		Units (£/unit for cost parameters)	2050 distribution range	
			2010	2050		Low	High
Storage	Battery - Li-ion	Capital Cost	668	267	kWh	−50%	50%
	Battery - NaS	Capital Cost	241	229	kWh	−10%	10%
	Compressed Air Storage of Electricity	Capital Cost	10	10	kWh	−30%	30%
	Flow battery - Redox	Capital Cost	443	266	kWh	−50%	50%
	Flow battery - Zn-Br	Capital Cost	280	252	kWh	−10%	10%
Power	Biomass Fired Generation	Capital Cost	2417	2357	kW	−10%	10%
	CCGT	Capital Cost	589	496	kW	−10%	10%
	CCGT with CCS	Capital Cost	997	777	kW	−42%	60%
	Gas Macro CHP	Capital Cost	562	489	kW	−10%	10%
	Geothermal Plant (EGS) Electricity & Heat	Capital Cost	9507	8556	kW	−50%	50%
	Geothermal Plant (HSA) Electricity & Heat	Capital Cost	25869	23282	kW	−30%	30%
	Geothermal Plant (HSA) Heat Only	Capital Cost	1459	1313	kW	−10%	10%
	H2 Turbine	Capital Cost	590	500	kW	−10%	10%
	IGCC Biomass	Capital Cost	1911	1507	kW	−50%	50%
	IGCC Biomass with CCS	Capital Cost	4069	2661	kW	−50%	50%
	IGCC Coal	Capital Cost	1827	1369	kW	−30%	30%
	IGCC Coal with CCS	Capital Cost	2343	1719	kW	−25%	100%
	Incineration of Waste	Capital Cost	1712	1472	kW	−10%	10%
	Nuclear (Gen III)	Capital Cost	6000	4200	kW	−20%	50%

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Table A1 (*continued*)

Technology type	Technology	Parameter type	Values		Units (£/unit for cost parameters)	2050 distribution range	
			2010	2050		Low	High
	Nuclear (Gen III)	Max annual build rate	1000	2000000	kW	−90%	25%
	Nuclear (Gen IV)	Capital Cost	6000	4200	kW	−20%	50%
	Nuclear (Gen IV)	Max annual build rate	100	240000	kW	−90%	25%
	Nuclear (small modular reactor, or SMR)	Capital Cost	6500	6500	kW	−20%	50%
	Nuclear (small modular reactor, or SMR)	Max annual build rate	100	1200000	kW	−100%	20%
	Offshore Wind (fixed)	Capital Cost	3000	1500	kW	−30%	15%
	Offshore Wind (floating)	Capital Cost	3000	1261	kW	−30%	15%
	Onshore Wind	Capital Cost	1489	1250	kW	−30%	30%
	PC Coal	Capital Cost	1565	1326	kW	−10%	10%
	PC Coal with CCS	Capital Cost	2868	2232	kW	−42%	60%
	Severn Barrage	Capital Cost	2330	2330	kW	−30%	50%
	Solar PV (Domestic)	Capital Cost	3300	673	kW	−30%	30%
	Solar PV (Farm)	Capital Cost	1400	449	kW	−30%	30%
	Tidal Range	Capital Cost	3030	2580	kW	−50%	50%
	Tidal Stream	Capital Cost	1890	1050	kW	−50%	50%
	Waste Gasification	Capital Cost	3750	3750	kW	−50%	50%
	Waste Gasification with CCS	Capital Cost	5800	5800	kW	−50%	50%
	Wave Power	Capital Cost	7810	3540	kW	−50%	50%
Fuel production	Biodiesel Production	Capital Cost	168	168	kW	−30%	30%
	Biokerosine Production	Capital Cost	219	219	kW	−50%	50%
	Biopetrol Production	Capital Cost	883	641	kW	−30%	30%
	Biopetrol Production with CCS	Capital Cost	883	671	kW	−30%	30%
	H2 Plant (Biomass Gasification with CCS)	Capital Cost	1204	828	kW	−50%	50%
	H2 Plant (Biomass Gasification)	Capital Cost	1061	763	kW	−50%	50%
	H2 Plant (Coal Gasification with CCS)	Capital Cost	950	698	kW	−50%	50%
	H2 Plant (Electrolysis)	Capital Cost	1266	611	kW	−30%	30%
	H2 Plant (steam methane reforming (SMR) with CCS)	Capital Cost	553	459	kW	−50%	50%
	SNG Plant (Biomass Gasification with CCS)	Capital Cost	1209	831	kW	−50%	50%
	SNG Plant (Biomass Gasification)	Capital Cost	969	764	kW	−50%	50%
Transport	Bus (BEV)	Capital Cost	182574	117300	vehicle	−50%	50%
	Bus (Dual Fuel Direct Flywheel Hybrid)	Capital Cost	152920	112579	vehicle	−30%	30%
	Bus (Dual Fuel Direct)	Capital Cost	146002	108100	vehicle	−30%	30%
	Bus (Dual Fuel Port)	Capital Cost	146002	110300	vehicle	−30%	30%
	Bus (Flywheel Hybrid)	Capital Cost	138085	110615	vehicle	−30%	30%
	Bus (Gas SI Flywheel Hybrid)	Capital Cost	148570	109252	vehicle	−30%	30%
	Bus (Gas SI)	Capital Cost	141002	104400	vehicle	−30%	30%
	Bus (Hybrid)	Capital Cost	224700	156600	vehicle	−30%	30%
	Bus (Hydrogen FCV)	Capital Cost	520000	153800	vehicle	−50%	50%
	Bus (ICE)	Capital Cost	130000	106400	vehicle	−10%	10%
	Bus (Wireless PHEV)	Capital Cost	165000	112700	vehicle	−30%	30%
	Car Battery (A/B Segment)	Capital Cost	18200	7567	vehicle	−10%	75%
	Car Battery (C/D Segment)	Capital Cost	25373	13161	vehicle	−10%	75%
	Car CNG (A/B Segment)	Capital Cost	10667	8186	vehicle	−10%	10%
	Car CNG (C/D Segment)	Capital Cost	16781	12949	vehicle	−10%	10%
	Car Hybrid (A/B Segment)	Capital Cost	10348	6125	vehicle	−10%	15%
	Car Hybrid (C/D Segment)	Capital Cost	15603	9146	vehicle	−10%	15%
	Car Hydrogen FCV (A/B Segment)	Capital Cost	33064	8192	vehicle	−10%	75%
	Car Hydrogen FCV (C/D Segment)	Capital Cost	52221	14234	vehicle	−10%	75%
	Car Hydrogen ICE (A/B Segment)	Capital Cost	29927	9207	vehicle	−10%	50%
	Car Hydrogen ICE (C/D Segment)	Capital Cost	47488	14847	vehicle	−10%	50%
	Car ICE (A/B Segment)	Capital Cost	7631	5662	vehicle	−10%	10%
	Car ICE (C/D Segment)	Capital Cost	11123	8456	vehicle	−10%	10%
	Car PHEV (A/B Segment)	Capital Cost	17710	6832	vehicle	−10%	25%
	Car PHEV (C/D Segment)	Capital Cost	26594	10328	vehicle	−10%	25%
	HGV (Dual Fuel Direct Flywheel Hybrid)	Capital Cost	97212	64767	vehicle	−30%	30%
	HGV (Dual Fuel Direct)	Capital Cost	92228	59253	vehicle	−30%	30%
	HGV (Dual Fuel Port)	Capital Cost	81807	58143	vehicle	−30%	30%
	HGV (Flywheel Hybrid)	Capital Cost	81109	60965	vehicle	−30%	30%
	HGV (Gas SI Flywheel Hybrid)	Capital Cost	83286	62200	vehicle	−30%	30%
	HGV (Gas SI)	Capital Cost	71807	56698	vehicle	−10%	10%
	HGV (Hydrogen FCV)	Capital Cost	1728053	455325	vehicle	−10%	75%
	HGV (ICE Euro 6)	Capital Cost	72337	57578	vehicle	−10%	10%
	LGV (BEV)	Capital Cost	65865	21200	vehicle	−10%	75%
	LGV (Dual Fuel Direct)	Capital Cost	39140	38640	vehicle	−10%	10%
	LGV (Dual Fuel Port)	Capital Cost	38140	37640	vehicle	−10%	10%
	LGV (Gas SI)	Capital Cost	31120	30620	vehicle	−10%	10%
	LGV (Hybrid)	Capital Cost	30290	16680	vehicle	−10%	10%
	LGV (Hydrogen FCV)	Capital Cost	84780	25737	vehicle	−10%	75%
	LGV (Hydrogen ICE)	Capital Cost	81911	28773	vehicle	−10%	50%
	LGV (ICE)	Capital Cost	21871	15350	vehicle	−10%	10%
	LGV (PHEV)	Capital Cost	36335	17050	vehicle	−10%	25%

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Table A1 (*continued*)

Technology type	Technology	Parameter type	Values 2010	Values 2050	Units (£/unit for cost parameters)	2050 distribution range Low	2050 distribution range High
	MGV (Dual Fuel Direct Flywheel Hybrid)	Capital Cost	61302	43621	vehicle	−30%	30%
	MGV (Dual Fuel Direct)	Capital Cost	59721	38369	vehicle	−30%	30%
	MGV (Dual Fuel Port)	Capital Cost	56350	40050	vehicle	−30%	30%
	MGV (Flywheel Hybrid)	Capital Cost	49446	39621	vehicle	−30%	30%
	MGV (Gas SI Flywheel Hybrid)	Capital Cost	52339	41928	vehicle	−30%	30%
	MGV (Gas SI)	Capital Cost	46350	36597	vehicle	−30%	30%
	MGV (Hydrogen FCV)	Capital Cost	1728053	455325	vehicle	−10%	75%
	MGV (ICE Euro 6)	Capital Cost	44779	35643	vehicle	−30%	30%
Buildings	District Heating (HD)	Capital Cost	3376–7059	3376–7059	dwelling	−30%	30%
	District Heating (MD)	Capital Cost	5818–9906	5818–9906	dwelling	−30%	30%
	District Heating (LD)	Capital Cost	8365–12903	8365–12903	dwelling	−30%	30%
	Retrofix (LD)	Capital Cost	16363	10187	dwelling	−20%	10%
	Retrofix (MD)	Capital Cost	11904	7284	dwelling	−20%	10%
	Retrofix (HD)	Capital Cost	7629	4917	dwelling	−20%	10%
	Retroplus (LD)	Capital Cost	25495	18237	dwelling	−20%	10%
	Retroplus (MD)	Capital Cost	18974	13608	dwelling	−20%	10%
	Retroplus (HD)	Capital Cost	14765	10246	dwelling	−20%	10%
	Heat Pump (Air Source, Hot Water)	Capital Cost	750	585	kW	−30%	30%
	Heat Pump (Air Source, Space Heat)	Capital Cost	750	585	kW	−30%	30%
	Heat Pump (Ground Source, Hot Water)	Capital Cost	1200	936	kW	−30%	30%
	Heat Pump (Ground Source, Space Heat)	Capital Cost	1200	936	kW	−30%	30%
	Heat Pump (Large Scale Marine)	Capital Cost	300	300	kW	−30%	30%
	Solar Thermal (Domestic non south facing)	Capital Cost	3046	2264	kW	−50%	50%
	Solar Thermal (Domestic south facing)	Capital Cost	1616	1249	kW	−50%	50%
Resources	Biomass Importing	Max annual build rate	1.08E+10	3.40E+10	kWh	−100%	200%
	Biofuel Imports	Resource Cost	6.01	5.46	p/kWh	−31%	50%
	Biomass Imports	Resource Cost	1.94	2.27	p/kWh	−21%	58%
	Coal	Resource Cost	0.78	0.61	p/kWh	−22%	51%
	Gas	Resource Cost	1.41	1.86	p/kWh	−39%	16%
	Liquid Fuel	Resource Cost	4.62	4.20	p/kWh	−31%	50%
	Nuclear	Resource Cost	0.16	0.34	p/kWh(th)	0%	39%
	UK Biomass	Resource Cost	1.87	1.87	p/kWh	−30%	30%
	UK Biomass	Max Resource Quantity	1.89E+10	1.17E+11	kWh	−30%	30%
	Industry CCS	Max annual build rate	1	100000	industrial units	−90%	50%
	Other CCS	Max annual build rate	100	20000000	kW	−90%	50%

A2. Metrics used in clustering analysis

These following metrics used in the technology clustering analysis (section 3.2) are taken directly from the model results, and consist of different energy technologies and resources, based on their use in the system (in generation or consumption terms).

Table A2a
Model scenario metrics using in technology clustering analysis

Metric	Units	Abbreviation
Marginal abatement cost	£/tCO2	SYS-MCC
Total discounted costs	£bln	SYS-TDC
Biomass system wide consumption	TWh	RSR-BIO
Coal system wide consumption	TWh	RSR-COA
Electricity system wide consumption	TWh	RSR-ELC
Gas system wide consumption	TWh	RSR-GAS
Oil system wide consumption	TWh	RSR-OIL
Wind generation level	TWh	ELC-WND
Nuclear generation level	TWh	ELC-NUC
CCS generation level	TWh	ELC-CCS
Other renewable generation level	TWh	ELC-ORE
Fossil generation level	TWh	ELC-FOS
Building bioenergy consumption	TWh	BLD-BIO
Building electricity consumption	TWh	BLD-ELC
Building gas consumption	TWh	BLD-GAS
Building oil consumption	TWh	BLD-OIL
Building district heating consumption	TWh	BLD-DH
Building solar energy consumption	TWh	BLD-SOL
CCS in biofuel production	MtCO2 captured	CCS-BFL
CCS in hydrogen production	MtCO2 captured	CCS-H2
CCS in industry	MtCO2 captured	CCS-IND
CCS in power generation	MtCO2 captured	CCS-ELC

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Table A2a (*continued*)

Metric	Units	Abbreviation
BECCS in biofuel production	MtCO2 captured	CCSB-BFL
BECCS in hydrogen production	MtCO2 captured	CCSB-H2
BECCS in industry	MtCO2 captured	CCSB-IND
BECCS in power generation	MtCO2 captured	CCSB-ELC
Retrofitted dwellings	000s dwellings	DWL-RTR
Imported biofuel	TWh	BFP-IMP
Domestic biofuel production	TWh	BFP-DOM
H2 production by biomass gasification with CCS	TWh	H2-BCCS
H2 production by coal gasification with CCS	TWh	H2-CCCS
H2 production by electrolysis	TWh	H2-ELC
H2 production by gas (steam methane reforming (SMR)) with CCS	TWh	H2-GCCS
H2 production by gas (steam methane reforming (SMR))	TWh	H2-GAS
Industry bioenergy consumption	TWh	IND-BIO
Industry coal consumption	TWh	IND-COA
Industry electricity consumption	TWh	IND-ELC
Industry gas consumption	TWh	IND-GAS
Industry hydrogen consumption	TWh	IND-H2
Industry oil consumption	TWh	IND-OIL
H2 storage	GWh	STR-H2
Building level storage	GWh	STR-BLD
District heating storage	GWh	STR-DH
Imported biofuel	TWh	BFL-IMP
Domestic biofuel production	TWh	BFL-DOM
Aviation & shipping - gas	TWh	TAS-GAS
Aviation & shipping - oil	TWh	TAS-OIL
Aviation & shipping - biofuel	TWh	TAS-BFL
Cars - electricity	TWh	TCAR-ELC
Cars - gas	TWh	TCAR-GAS
Cars - H2	TWh	TCAR-H2
Cars - oil	TWh	TCAR-OIL
Cars - biofuels	TWh	TCAR-BFL
Heavy goods vehicles - electricity	TWh	THGV-ELC
Heavy goods vehicles - gas	TWh	THGV-GAS
Heavy goods vehicles - H2	TWh	THGV-H2
Heavy goods vehicles – oil	TWh	THGV-OIL
Heavy goods vehicles - biofuels	TWh	THGV-BFL
Light goods vehicles - electricity	TWh	TLGV-ELC
Light goods vehicles - H2	TWh	TLGV-H2
Light goods vehicles - oil	TWh	TLGV-OIL
Light goods vehicles - biofuels	TWh	TLGV-BFL
Other transport - electricity	TWh	TOTH-ELC
Other transport - gas	TWh	TOTH-GAS
Other transport - H2	TWh	TOTH-H2
Other transport - oil	TWh	TOTH-OIL
Other transport - biofuels	TWh	TOTH-BFL

This following LMDI derived mitigation wedges provide an indicator of the contribution of different types of mitigation across sectors (as used in section 3.1). These wedges allocate emission reductions across different sectors to three different types of measures: (1) Reduction of energy demands (2) improvements in efficiency and (3) decarbonisation.

Table A2b
LMDI metrics using in mitigation wedge clustering analysis

Sector	Mitigation wedge	Abbreviation
Buildings – heat	Demand reduction	BLDH_DEM
Buildings – heat	End use efficiency	BLDH_EE
Buildings – heat	Decarbonisation	BLDH_DCB
Industry	Demand reduction	IND_DEM
Industry	End use efficiency	IND_EE
Industry	Decarbonisation	IND_DCB
Transport – aviation	Demand reduction	TAV_DEM
Transport – aviation	End use efficiency	TAV_EE
Transport – aviation	Decarbonisation	TAV_DCB
Transport – car	Demand reduction	TCR_DEM
Transport – car	End use efficiency	TCR_EE
Transport – car	Decarbonisation	TCR_DCB
Transport – road freight	Demand reduction	TFR_DEM
Transport - road freight	End use efficiency	TFR_EE
Transport - road freight	Decarbonisation	TFR_DCB
Transport – shipping	Demand reduction	TSP_DEM
Transport – shipping	End use efficiency	TSP_EE

(*continued on next page*)

Table A2b (*continued*)

Sector	Mitigation wedge	Abbreviation
Transport - shipping	Decarbonisation	TSP_DCB
Power generation	Conversion efficiency	PWR_CEF
Power generation	Decarbonisation	PWR_DCB
Conv - biofuel production	Decarbonisation (based on FE)	CBF_DEM
Conv - biofuel production	Conversion efficiency	CBF_CEF
Conv - biofuel production	Decarbonisation	CBF_DCB
Conv - district heating	Decarbonisation (based on FE)	CDH_DEM
Conv - district heating	Conversion efficiency	CDH_CEF
Conv - district heating	Decarbonisation	CDH_DCB
Conv - H2 production	Decarbonisation (based on FE)	CH2_DEM
Conv - H2 production	Conversion efficiency	CH2_CEF
Conv - H2 production	Decarbonisation	CH2_DCB
Conv - Other	Decarbonisation (based on FE)	COT_DEM
Conv - Other	Conversion efficiency	COT_CEF
Conv - Other	Decarbonisation	COT_DCB

A3. Technology clustering results

The following tables describe the clusters of technologies under each of the scenarios, and the negatively correlated clusters. These are the results presented in section 3.2.

Table A3a
NCCS cluster descriptions. Negatively correlated clusters identified where the coefficient value is greater than 0.5

Cluster colour	Cluster name	Cluster metrics	Negatively correlated clusters
Purple	Transport biofuels and gas	System wide biomass and gas use; domestic biofuel production and use across modes; oil and gas us in freight (in addition to biofuels)	Orange (−0.87)
Sky blue	Transport electrification	Electricity use across road transport (passenger and freight)	None
Green	RE with H_2 storage	Wind and other renewables; H_2 storage	None (but strong with nuclear generation)
Blue	District heating	District heating (and storage). Clustered with 2 metrics of transport biofuel use but weak correlation.	Yellow (−0.98)
Yellow	Building electrification	Electrification of the building stock; storage capacity in buildings (hot water); building retrofit; nuclear generation.	Blue (−0.98)
Orange	H_2 for transport	H_2 production via electricity; H2 in passenger road transport; cost metrics; oil in aviation; system wide oil use	Purple (−0.87)

Table A3b
CP cluster descriptions. Negatively correlated clusters identified where the coefficient value is greater than 0.5

Cluster colour	Cluster name	Cluster metrics	Negatively correlated clusters
Orange	H_2 production with gas for transport	H_2 production (via gas steam methane reforming (SMR)) and use in the transport sector.	Brown (−0.51)
Green	Renewable generation	Renewable power generation options, costs metrics, selected transport electrification.	Brown (−0.48)
Sky blue	Passenger car electrification	Passenger transport electrification; system electricity; aviation biofuels.	Brown (−0.66)
Brown	H_2 with bio CCS, car oil use	Biomass resource; H_2 production with CCS & bioenergy; oil in cars; system oil use; H2 and oil use in industry.	Orange (−0.51), Green (−0.48), Sky blue (−0.66)
Pink	Building electrification, power gen. w/CCS	Electrification of buildings – as per the description in Table A3a; CCS in power sector, and system gas use.	Blue (−0.94)
Blue	District heating	District heating (and storage). Clustered with transport biofuel use but weak correlation.	Pink (−0.94)

Table A3c
F2R cluster descriptions. Negatively correlated clusters identified where the coefficient value is greater than 0.5.

Cluster colour	Cluster name	Cluster metrics	Negatively correlated clusters
Green	Non-CCS generation	Generation types including nuclear, wind and other renewables	Pale pink (−0.84)
Pink	Biofuel production (w/CCS)	Biofuel production with use across the transport sector	Brown (−0.85)
Brown	H_2 with CCS, transport oil use	As per purple cluster under CP (Table A3b), except for biomass resource.	Pink (−0.85)
Olive green	Biomass resource	Biomass availability; industry biomass; gas use in buildings.	Yellow (−0.76)
Yellow	End use sector decarbonisation	System electricity; building sector electrification; H_2 in industry; system costs.	Olive green (−0.76)
Pale pink	Gas CCS	System gas use; electricity generation with CCS (as in pink CP cluster).	Green (−0.84)

(*continued on next page*)

Table A3c (*continued*)

Cluster colour	Cluster name	Cluster metrics	Negatively correlated clusters
Blue	District heating	District heating (and storage). As in NCCS/CP, clustered with transport biofuel use but weak correlation.	

The following figures show the dendrograms based on the technology clustering analysis (section 3.2), by scenario. The different colours in the figures denote the clusters, based on a predetermined ten cluster set. The dissimilarity score, at the lowest level between two metrics, is estimated as (1 – [correlation coefficient between two metrics]), with very low values suggesting a high positive correlation. As clusters begin to grow through aggregating individual metrics/subsets of metrics, the dissimilarity value is recalculated to represent the relationship between two clusters, instead of the relationship between individual technologies in the two clusters. A dissimilarity score of 2 between two larger clusters indicates that there is a higher chance that a technology in one cluster will have a negative correlation with a technology in the other cluster.

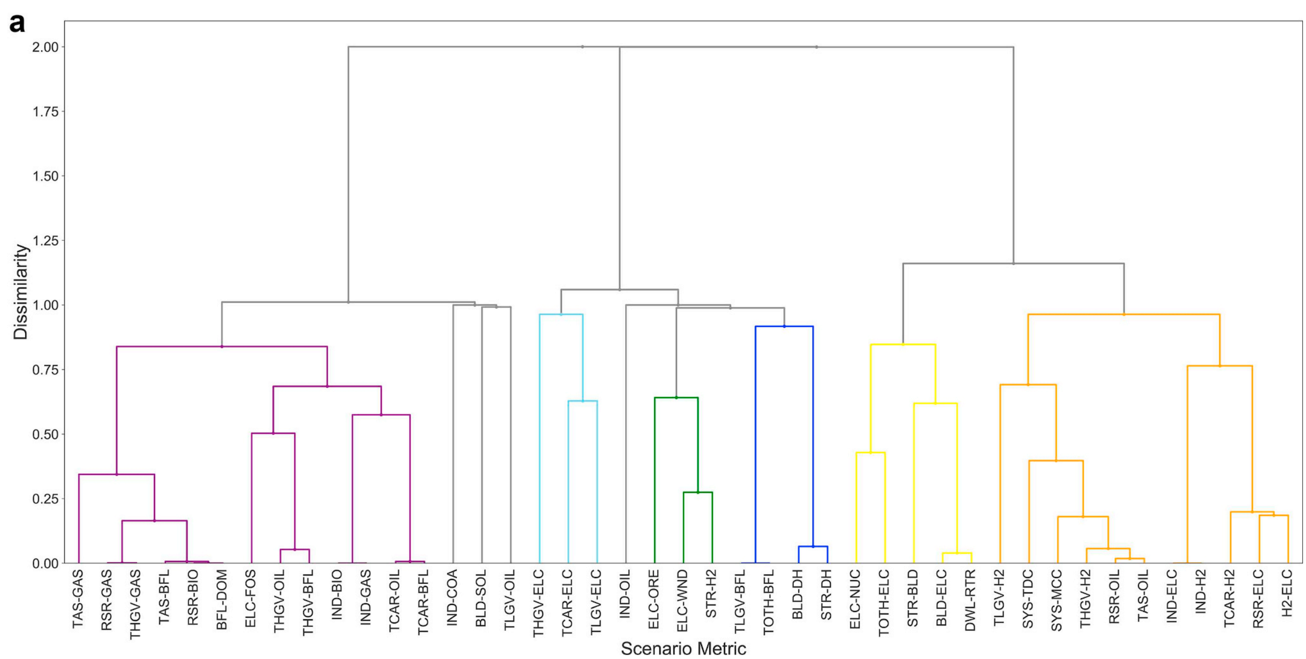
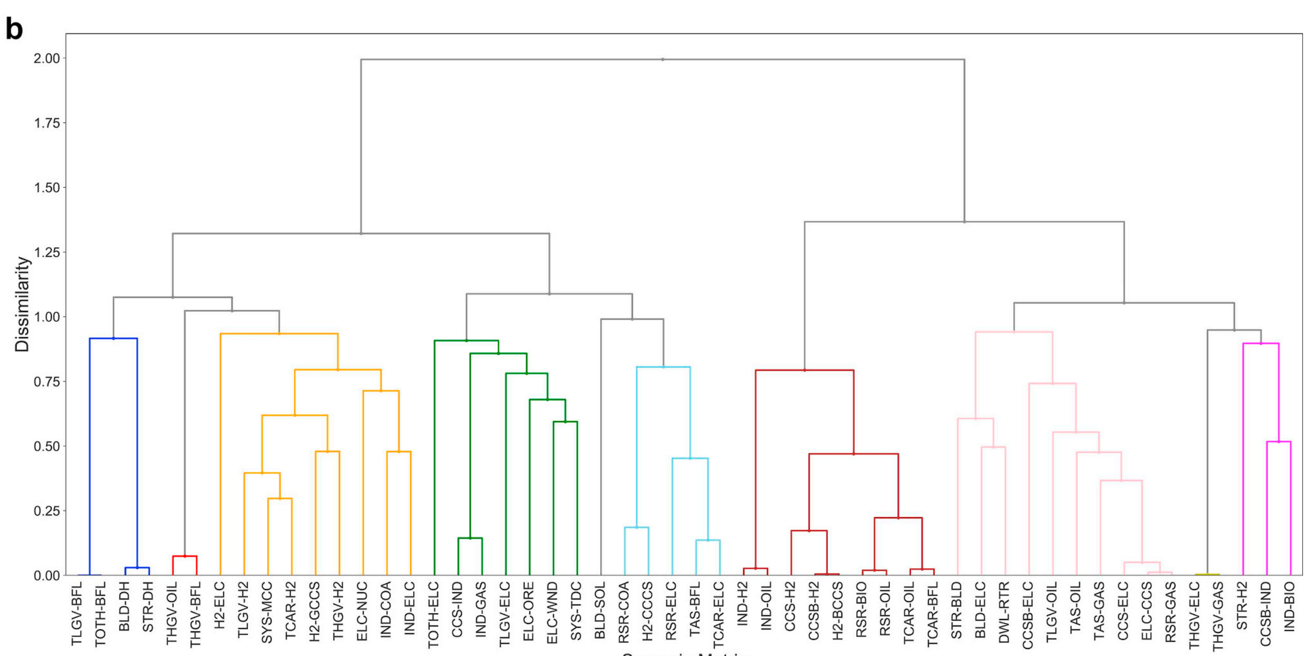
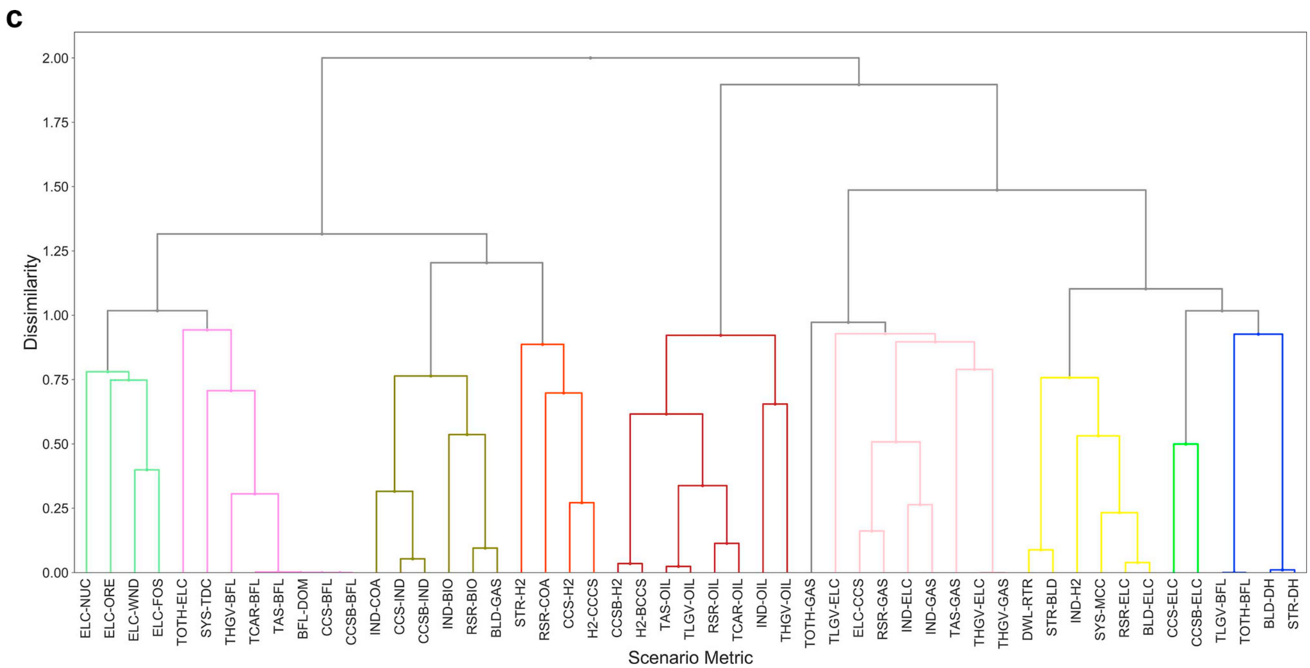


Fig. A3a-c. Hierarchical clustering dendrogram of ESME simulations in 2050 for each scenario. Note that the lower the dissimilarity score, the stronger the positive correlation. The low dissimilarity scores for pairs of industrial fuels reflect very limited variation between simulations and are excluded from the results descriptions.




c
Dissimilarity
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
ELC-NUC
ELC-ORE
ELC-WND
ELC-FOS
TOTH-ELC
SYS-TDC
THGV-BFL
TCAR-BFL
TAS-BFL
BFL-DOM
CCS-BFL
CCSB-BFL
IND-COA
CCS-IND
CCSB-IND
IND-BIO
RSR-BIO
BLD-GAS
STR-H2
RSR-COA
CCS-H2
H2-CCCS
CCSB-H2
H2-BCCS
TAS-OIL
TLGV-OIL
RSR-OIL
TCAR-OIL
IND-OIL
THGV-OIL
TOTH-GAS
TLGV-ELC
ELC-CCS
RSR-GAS
IND-ELC
IND-GAS
TAS-GAS
THGV-ELC
THGV-GAS
DWL-RTR
STR-BLD
IND-H2
SYS-MCC
RSR-ELC
BLD-ELC
CCS-ELC
CCSB-ELC
TLGV-BFL
TOTH-BFL
BLD-DH
STR-DH
Scenario Metric

A4. Correlations between mitigation wedges (used in the LMDI analysis)

NCCS

	BLDH_EE(30)	BLDH_DCB(30)	IND_DCB(30)	TAV_DEM(30)	TCR_DEM(30)	TCR_EE(30)	PWR_DCB(30)	CBF_DEM(30)	CBF_DCB(30)	BLDH_DCB(50)	TCR_EE(50)	TCR_DCB(50)	PWR_DCB(50)
BLDH_EE(30)		-0.03	-0.94	-0.97	-0.97	0.76	0.95	-0.06	0.06	0.95	0.66	0.13	0.80
BLDH_DCB(30)	-0.03		-0.25	-0.16	-0.17	0.07	-0.02	0.03	-0.04	0.15	0.07	0.00	0.20
IND_DCB(30)	-0.94	-0.25		0.98	0.97	-0.79	-0.93	0.03	-0.03	-0.98	-0.62	-0.22	-0.88
TAV_DEM(30)	-0.97	-0.16	0.98		1.00	-0.77	-0.95	0.05	-0.05	-0.99	-0.65	-0.16	-0.86
TCR_DEM(30)	-0.97	-0.17	0.97	1.00		-0.72	-0.95	0.05	-0.05	-0.98	-0.66	-0.12	-0.85
TCR_EE(30)	0.76	0.07	-0.79	-0.77	-0.72		0.70	-0.03	0.03	0.78	0.44	0.49	0.67
PWR_DCB(30)	0.95	-0.02	-0.93	-0.95	-0.95	0.70		-0.03	0.03	0.95	0.58	0.20	0.88
CBF_DEM(30)	-0.06	0.03	0.03	0.05	0.05	-0.03	-0.03		-0.98	-0.05	-0.07	0.10	0.00
CBF_DCB(30)	0.06	-0.04	-0.03	-0.05	-0.05	0.03	0.03	-0.98		0.05	0.07	-0.09	0.00
BLDH_DCB(50)	0.95	0.15	-0.98	-0.99	-0.98	0.78	0.95	-0.05	0.05		0.62	0.22	0.88
TCR_EE(50)	0.66	0.07	-0.62	-0.65	-0.66	0.44	0.58	-0.07	0.07	0.62		-0.47	0.46
TCR_DCB(50)	0.13	0.00	-0.22	-0.16	-0.12	0.49	0.20	0.10	-0.09	0.22	-0.47		0.28
PWR_DCB(50)	0.80	0.20	-0.88	-0.86	-0.85	0.67	0.88	0.00	0.00	0.88	0.46	0.28	

CP

	BLDH_EE(30)	BLDH_DCB(30)	IND_DCB(30)	TCR_EE(30)	PWR_DCB(30)	CH2_DEM(30)	CH2_DCB(30)	BLDH_DCB(50)	IND_DCB(50)	TCR_EE(50)	TCR_DCB(50)	PWR_DCB(50)
BLDH_EE(30)		-0.03	-0.94	0.76	0.95	-0.41	0.46	0.95	-0.80	0.66	0.13	0.80
BLDH_DCB(30)	-0.03		-0.25	0.07	-0.02	-0.06	0.07	0.15	-0.13	0.07	0.00	0.20
IND_DCB(30)	-0.94	-0.25		-0.79	-0.93	0.32	-0.37	-0.98	0.87	-0.62	-0.22	-0.88
TCR_EE(30)	0.76	0.07	-0.79		0.70	0.00	0.05	0.78	-0.83	0.44	0.49	0.67
PWR_DCB(30)	0.95	-0.02	-0.93	0.70		-0.33	0.37	0.95	-0.84	0.58	0.20	0.88
CH2_DEM(30)	-0.41	-0.06	0.32	0.00	-0.33		-1.00	-0.33	-0.13	-0.58	0.68	-0.12
CH2_DCB(30)	0.46	0.07	-0.37	0.05	0.37	-1.00		0.38	0.07	0.60	-0.65	0.17
BLDH_DCB(50)	0.95	0.15	-0.98	0.78	0.95	-0.33	0.38		-0.87	0.62	0.22	0.88
IND_DCB(50)	-0.80	-0.13	0.87	-0.83	-0.84	-0.13	0.07	-0.87		-0.31	-0.61	-0.86
TCR_EE(50)	0.66	0.07	-0.62	0.44	0.58	-0.58	0.60	0.62	-0.31		-0.47	0.46
TCR_DCB(50)	0.13	0.00	-0.22	0.49	0.20	0.68	-0.65	0.22	-0.61	-0.47		0.28
PWR_DCB(50)	0.80	0.20	-0.88	0.67	0.88	-0.12	0.17	0.88	-0.86	0.46	0.28	

F2R

	BLDH_EE(30)	IND_DCB(30)	TAV_EE(30)	TCR_EE(30)	PWR_DEM(30)	PWR_CEF(30)	PWR_DCB(30)	CBF_DEM(30)	CBF_CEF(30)	CBF_DCB(30)	CH2_DEM(30)	CH2_DCB(30)	BLDH_EE(50)	BLDH_DCB(50)	IND_DCB(50)	TAV_EE(50)	TCR_EE(50)	PWR_DCB(50)
BLDH_EE(30)		-0.94	0.97	0.76	-0.12	0.17	0.95	-0.06	-0.06	0.06	-0.41	0.46	0.54	0.95	-0.80	0.69	0.66	0.80
IND_DCB(30)	-0.94		-0.98	-0.79	0.25	-0.33	-0.93	0.03	0.03	-0.03	0.32	-0.37	-0.44	-0.98	0.87	-0.74	-0.62	-0.88
TAV_EE(30)	0.97	-0.98		0.77	-0.19	0.22	0.95	-0.05	-0.05	0.05	-0.39	0.44	0.45	0.99	-0.84	0.73	0.65	0.86
TCR_EE(30)	0.76	-0.79	0.77		-0.34	0.25	0.70	-0.03	-0.03	0.03	0.00	0.05	0.37	0.78	-0.83	0.54	0.44	0.67
PWR_DEM(30)	-0.12	0.25	-0.19	-0.34		-0.38	-0.28	-0.11	-0.11	0.11	-0.33	0.31	0.28	-0.25	0.42	-0.28	0.06	-0.38
PWR_CEF(30)	0.17	-0.33	0.22	0.25	-0.38		0.20	-0.01	-0.01	0.01	0.04	-0.02	0.05	0.29	-0.31	0.25	0.16	0.28
PWR_DCB(30)	0.95	-0.93	0.95	0.70	-0.28	0.20		-0.03	-0.03	0.03	-0.33	0.37	0.40	0.95	-0.84	0.74	0.58	0.88
CBF_DEM(30)	-0.06	0.03	-0.05	-0.03	-0.11	-0.01	-0.03		1.00	-0.98	0.16	-0.17	0.01	-0.05	-0.02	-0.01	-0.07	0.00
CBF_CEF(30)	-0.06	0.03	-0.05	-0.03	-0.11	-0.01	-0.03	1.00		-0.96	0.16	-0.17	0.01	-0.05	-0.02	-0.01	-0.07	0.00
CBF_DCB(30)	0.06	-0.03	0.05	0.03	0.11	0.01	0.03	-0.98	-0.96		-0.15	0.16	-0.02	0.05	0.02	0.01	0.07	0.00
CH2_DEM(30)	-0.41	0.32	-0.39	0.00	-0.33	0.04	-0.33	0.16	0.16	-0.15		-1.00	-0.27	-0.33	-0.13	0.04	-0.58	-0.12
CH2_DCB(30)	0.46	-0.37	0.44	0.05	0.31	-0.02	0.37	-0.17	-0.17	0.16	-1.00		0.29	0.38	0.07	0.01	0.60	0.17
BLDH_EE(50)	0.54	-0.44	0.45	0.37	0.28	0.05	0.40	0.01	0.01	-0.02	-0.27	0.29		0.37	-0.33	0.27	0.37	0.29
BLDH_DCB(50)	0.95	-0.98	0.99	0.78	-0.25	0.29	0.95	-0.05	-0.05	0.05	-0.33	0.38	0.37		-0.87	0.76	0.62	0.88
IND_DCB(50)	-0.80	0.87	-0.84	-0.83	0.42	-0.31	-0.84	-0.02	-0.02	0.02	-0.13	0.07	-0.33	-0.87		-0.82	-0.31	-0.86
TAV_EE(50)	0.69	-0.74	0.73	0.54	-0.28	0.25	0.74	-0.01	-0.01	0.01	0.04	0.01	0.27	0.76	-0.82		0.27	0.76
TCR_EE(50)	0.66	-0.62	0.65	0.44	0.06	0.16	0.58	-0.07	-0.07	0.07	-0.58	0.60	0.37	0.62	-0.31	0.27		0.46
PWR_DCB(50)	0.80	-0.88	0.86	0.67	-0.38	0.28	0.88	0.00	0.00	0.00	-0.12	0.17	0.29	0.88	-0.86	0.76	0.46	

Fig. A4. Correlations between mitigation wedges in RM (top panel), NCCS (middle panel) and F2R (bottom panel). Wedges for 2030 and 2050 both are given and only the ones with at least 10% share for the milestone year in at least one run are included. Correlations above 0.8 and below −0.8 are highlighted. Fill colours indicate over 10% share in at least one run for 2030 only (yellow), for 2050 only (blue) or for both 2030 and 2050 (green).

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